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A Cyber-physical System Architecture in Shop Floor for Intelligent Manufacturing

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Abstract

A Cyber-physical System (CPS) architecture in shop floor is proposed for achieving the goals of intelligent manufacturing. The proposed architecture provides a guideline to construct a CPS system from the hardware interconnection, to the data acquisition, processing, and visualization, and the final knowledge acquisition and learning. Furthermore, three key enabling technologies are discussed, *i.e.*, interconnection and interoperability among different devices, industrial big data analysis for production process management and control, and intelligent decision-making based on knowledge acquisition and learning methodology. Finally, a CPS added on a small-scale flexible automated production line in our Micro Manufacturing System Lab is taken as an example to verify the feasibility of proposed CPS architecture.

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Keywords: cyber-physical system; intelligent manufacturing; industrial big data; knowledge learning

1. Introduction

During the past decade, the rapid advancement of Information and Communication Technologies (ICT) has boosted the development of advanced sensors, data acquisition system, wireless communication devices and distributed computing solutions. Such technologies are integrated into a new system called Cyber-physical System (CPS). CPS is a system of collaborating computational entities which are in intensive connection with the surrounding physical world and its on-going processes, providing and using, at the same time, data-accessing and data-processing services available on the internet [1]. CPS has caught ever-growing attentions of researchers from academia, industry, and government in recent years. Currently, a precursor generation of CPS can be found in areas as diverse as aerospace, automotive, civil infrastructure, chemical processes, energy, healthcare, transportation and manufacturing [2].

As a technology base for building intelligent manufacturing environment, CPS is introduced into the shop floor, providing factories with continuous production, near-zero downtime and intelligent decision-making in manufacturing process [3]. In such an intelligent manufacturing shop floor, machine tools and their auxiliaries, industrial robots, Automatic Guided Vehicles (AGVs) and staffs constitute the manufacturing resources (physical space). Manufacturing data is collected from the sensors/RFID devices/measurement devices deployed on these manufacturing resources, which constitute the cyber space. Often, a communication channel is involved to transmit data that are used to monitor and control the manufacturing resources. On the cyber side, computations are carried out with the objective of achieving high quality, flexible production and reduced cost, based on which intelligent decisions are taken and the manufacturing resources are adaptively controlled. Thus, the expectations on self-awareness and self-maintenance of manufacturing resources, and intelligent adaptive control of manufacturing processes can be realized by integrating CPS with production, logistics as well as industrial services [4, 5].

According to Dwnrschak and Zaiser' survey [6], the degree of CPS implementation in manufacturing enterprises has been fairly low, so it is essential to put forward a universal architecture as a step-by-step guideline for developing and configuring a CPS for shop floor. However, several challenges

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exist in the development of CPS [7]. For example, to enable seamless integration between cyber space and physical space, the events occurred in the physical space need to be reflected in the cyber space, and the production commands given by the cyber space need to be communicated to the physical systems. Both these actions need to be accurately performed and in a timely manner. Furthermore, sensors (*e.g.*, force, vibration) monitoring manufacturing processes that work at high sampling rates can generate a large amount of data within a short time period. However, many manufacturing systems are not ready to manage big data due to the lack of smart analytic tools [2].

To address the issues mentioned above, a CPS architecture in shop floor for intelligent manufacturing is proposed in this paper, and then three key enabling technologies are considered for CPS implementation, *i.e.*, (1) interconnection and interoperability among heterogeneous devices which ensure the real-time data acquisition from production environment and production commands feedback from the cyber space; (2) management, analysis of multi-source and heterogeneous big data; (3) knowledge acquisition and learning methodology that supports intelligent decision-making. Finally, a CPS added on a small-scale flexible automated production line in our Micro Manufacturing System Lab is taken as an example to verify the feasibility of proposed CPS architecture.

2. CPS architecture for intelligent manufacturing

Fig.1 depicts a CPS architecture in shop floor for intelligent manufacturing and it includes three layers, *i.e.*, physical connection layer, middleware layer and computation layer. The explanation of each layer is presented as follows.

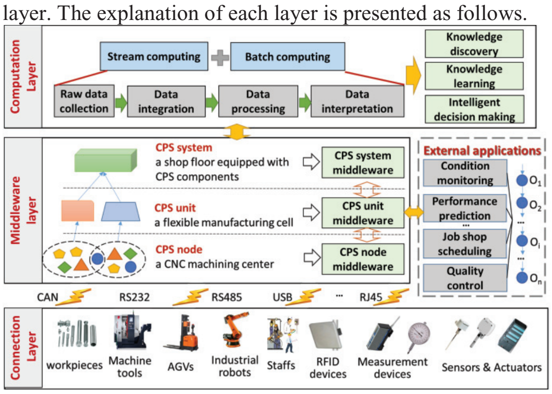

Fig. 1. CPS architecture for intelligent manufacturing.

2.1. Physical connection layer

Sensors are the machine's gateway to sense its surrounding physical environment. Using appropriate sensor installation, various signals such as vibration, pressure, temperature can be extracted. So the first step of CPS implementation in shop floor is to embed components like sensors, RFID devices and measurement devices on the manufacturing resources and distribute them in the production environment. Then a group of machines are connected with each other through fieldbus technology and/or industrial Ethernet. In this layer, issues about protocol, processing, location, distance, and storage need to be considered when the embedded component is chosen. For example, the uniform and robust connections between heterogeneous physical entities (*e.g.*, manufacturing resources, sensors, actuators, and measurement devices) should be defined; proper sensors (type and specification) should be selected and deployed on proper locations with low cost and high efficiency on the basis of historical machining tasks.

2.2. Middleware layer

This layer aims to transfer the data collected from the embedded components to the central server for analysis, and send the production commands given by computation layer or external applications (*e.g.*, condition monitoring, dynamic job scheduling, and quality control) to controllers for control. Therefore, CPS middleware acts as a bond among physical connection layer, computation layer and external applications. According to the above descriptions, the middleware must support the following functions:

Device management. Different external applications are likely to use different sensors/RFID devices/measurement devices which have different brands and types. Moreover, these devices have their own communication protocols and standards. Thus, a public device management module is needed to drive these multiple devices work together, and eventually achieve the goal of plug and play.

Interface definition. The data interface provides a channel for CPS node communications, and required data/information to the computation layer and external applications, hiding all the details of diversity.

Data management. The data collected from sensors/RFID devices/measurement devices can be production environment state (e.g., temperature, humidity, and noise), machine working condition (e.g., power, speed, and vibration), workpiece state and quality data (e.g., location, size, roughness, and tolerance), etc. The potentially large variety of data types and formats necessitates a uniform data format and data exchange standard to manage data in context with process-related information in the shop floor.

2.3. Computation layer

A large amount of data, real-time online or historical offline, is gathered by various sensors/RFID devices/measurement devices, or obtained from Enterprise Information Systems (EIS) such as ERP, MES, and SCM. Specific models, algorithms and tools have to be used to extract underlying patterns that provide better insight over machine working conditions, workpiece quality, manufacturing processes, *etc*. Take job shop scheduling as an example, the dispatching rules are incorporated with the data obtained from online measurement, data processing, or data fusion, which makes sense especially when machines works in a complex production environment and undergoes a different deterioration rate. In this layer, two forms of big data computing that need to be addressed are batch computing and stream computing. Batch computing is used to process large volumes of historical data, and stream computing is used to process the data stream obtained from sensors. After batch computing or stream computing, the results are transmitted back to the machine site for operation/process control and maintenance. So this layer acts as supervisory control to make machines or manufacturing process self-adaptive and self-ware.

On the other hand, substantial knowledge about machine operation behavior and production process has been extracted by data mining when implementing CPS in shop floor. This layer takes responsibility for integrating the generated knowledge with humans' experience, thereby creating a unified view of data, information and knowledge to support intelligent decision-making. By applying a knowledge acquisition and learning methodology to production process management, CPS will grow more intelligent as more manufacturing tasks are executed.

3. Key enabling technologies

To better implement the CPS in shop floor, three key enabling technologies are discussed, *i.e.*, the interconnection and interoperability among different devices, the industrial big data analysis for production process management and control, and the intelligent decision-making based on knowledge acquisition and learning methodology.

3.1. Interconnection and interoperability among different devices

Due to the variety and heterogeneity of machines and systems, the collected data have multi-source and heterogeneous characteristics. Therefore, the unified data format and interface need to be properly defined, so that the obtained data can be recorded and managed, and every networked machine or device can be interacted with each other under the circumstance of different communication protocols (*e.g.*, Modbus, Fieldbus, Profibus, or TCP/IP). With the help of Semantic Web technologies, a semantic middleware for interoperability among heterogeneous devices in the context of the Internet of Things (IoT) was proposed by Song [8]. This middleware hides complicated device details from users and does not require any changes to the existing devices. In this research, a general middleware for implementing the CPS is developed as shown in Fig. 2. Three key procedures for the development of the proposed middleware are included: abstraction of CPS component, node, unit and system, definition of data interface, and data management.

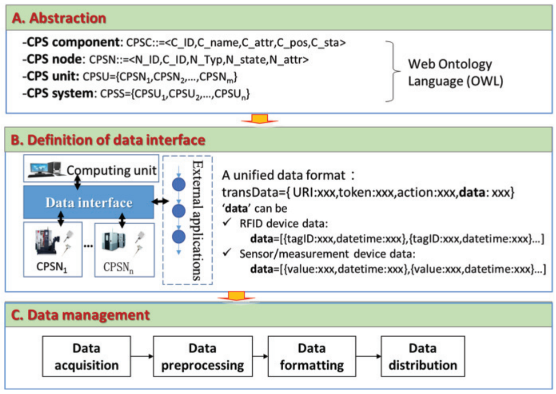

Fig. 2. Development of a general middleware.

- *Abstraction*

In order to manage the CPS entities efficiently, the CPS is structured as four levels, *i.e.*, CPS component, node, unit and system. The detailed description is presented as follows.

CPS component is the element of CPS, and it consists of sensors, actuators, controllers and computers and so on.

CPS node refers to the integrations between a machine (machine tool, AGV, industrial robot, *etc.*) and CPS components. CPS node is the smallest CPS structure which has the capabilities of sensing, computing, communication, decision making and control. A CNC machining center can be regarded as a CPS node.

CPS unit is the organic combination of different CPS nodes, physically or logically. CPS unit is used to finish a specific machining task. A flexible manufacturing cell can be regarded as a CPS unit.

CPS system is the collection of all the CPS units. In this study, CPS system refers to the shop floor that is equipped with CPS components.

Corresponding to the different levels of CPS, the developed middleware is categorized into CPS node middleware, CPS unit middleware, and CPS system middleware. Before designing and developing each level of middleware, a unified terminology is utilized to construct the information model of the CPS component, CPS node, CPS unit and CPS system (see Fig. 2). In this research, Web Ontology Language (OWL) can be used to represent the CPS component, node, unit and system, and the complex relationships among them.

- *Definition of data interface*

After having representing the CPS node, unit and system, the next step is to define the data interface. As shown in Fig.2, the interface consists of three kinds of types. Sense interface is used to access multiple devices with different communication protocols. Computing interface and application interface provide a unified data format for computation layer and external applications, respectively. The common data exchange format includes XML, JSON, CSV, *etc*. For example, the collected data can be structured as a unified data format by JSON (see Fig. 2).

- *Data management*

Data management module consists of the following four steps:

Data acquisition. During the operation process of CPS, when and where to collect certain data is determined by the manufacturing execution logic which is presented in the form of various external applications. Note that the collected data may be inaccurate and unreliable, and it is merely a sequence of characters with no physical meaning.

Data preprocessing. The data preprocessing operation is conducted on the acquired data, such as checkout, debugging, duplicate checking, duplicate removal, and finally the useful data can be obtained.

Data formatting. The process of formatting includes two implications: endowing the measured data with specific physical meanings and enabling the data to be a unified format.

Data distribution. There are two scenes of data distribution. In the first scene, the predefined event is triggered when the monitoring data changes, and event data is transferred to applications which subscribe to the event. In the second scene, the computation layer and external applications require sensor data from middleware by production commands.

3.2. Industrial big data analysis for manufacturing process

The gathered data can provide opportunities for remote monitoring, diagnosis, and quality control by providing a holistic perspective of the historical and current state of machines and manufacturing process. However, there are lots of challenges when CPS and big data encounter [9]. The quantity of data is big but the quality is low and the data is heterogeneous. Furthermore, the manufacturing process requires high speed and real-time responses to changes (*e.g.*, machine breakdown, order inserting) in production environment. An industrial big data analysis framework for manufacturing process is proposed to discover the potentially useful patterns and extract hidden information. The framework includes four steps, as shown in Fig. 3.

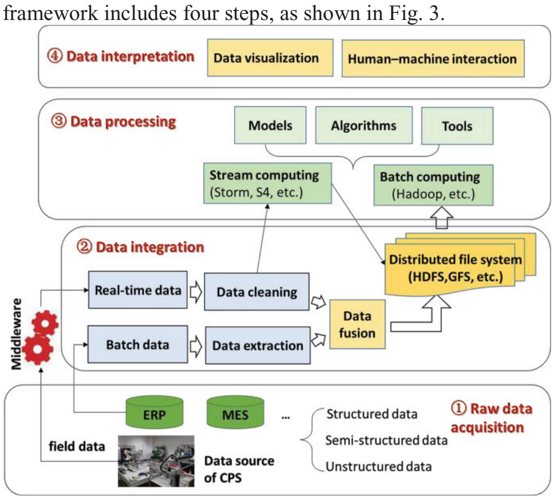

Fig. 3. An industrial big data analysis framework for manufacturing process.

- *Raw data acquisition*

As stated before, the raw data have the characteristics of multisource and heterogeneity, which means that these data can be obtained from CPS, ERP, MES, *etc*. And the obtained data can be structured, semi-structured, and even entirely unstructured.

- *Data integration*

Due to the limitation in network bandwidth, it is impractical to directly transmit raw data form individual machines to the storage center. So, before the transmission, a cost-effective approach must be used to remove the outliers. As shown in Fig. 3, real-time data is achieved from sensors/RFID devices/measurement devices through the middleware, and then the data cleaning and noise elimination are carried out because of duplicated, missing and uncompleted records. On the other hand, batch data from ERP, MES, *etc*., are extracted, and then it is merged with the real-time data. The merged data are transmitted to a distributed file system such as Hadoop Distributed File System (HDFS) and Google File System (GFS) for data processing.

- *Data processing*

There are two forms of big data computing, *i.e*., stream computing and batch computing. Stream computing is used to process the real-time data from the production site; a typical application is condition monitoring of machines. Batch computing processes large volumes of historical data, by which hidden knowledge can be discovered. A typical application for batch computing is mining dispatching rules. On the other hand, specific models, algorithms, tools are considered in this step. Models are the abstraction of the concrete problems to be solved. For example, in order to predict the Remaining Useful Life (RUL) of cutting tools, the wear mechanism in metal cutting must be studied. Algorithms are designed to solve the model. In industrial big data environment, traditional data mining algorithms need to be modified so as to meet the requirements of large scale computing. Currently, lots of open source tools such as Storm, Spark and Hadoop are available on the Internet to support the industrial big data analysis.

- *Data interpretation*

In order to convey results clearly and efficiently to end users (operators, managers, *etc*.), the data visualization technologies such as statistical graphics, plots, information graphics, tables, and charts are utilized. Human-machine interaction technology is also used to help users to better understand the presented results.

3.3. Intelligent decision-making based on knowledge acquisition and learning methodology

The operation of CPS during the manufacturing process can generate large amounts of manufacturing data, interactive behavior and decision-making information in which knowledge on process planning, machine tool performance, dispatching rule is hidden. To harvest the hidden knowledge and make the system more intelligent, a methodology of knowledge acquisition, learning, updating, transmission and sharing is necessary. Therefore, a knowledge acquisition and learning framework is proposed, as shown in the top of Fig. 4. Firstly, a great deal of human experience in production is transformed into the structured domain knowledge by using a unified knowledge representation approach such as production rule system, semantic web. Then the acquired knowledge is added to the knowledge base which provides decision-making knowledge for employees, and the employees' production experience is accumulated continually. At the same time, the knowledge learning system is operated by using the historical data from the knowledge base and the real-time data from the CPS. Under the guidance and supervision of high-skilled employees (production managers, process engineers, software engineers), the CPS keeps learning and becomes more and more intelligent. Thus, the evolvement of CPS operation in shop floor from immaturity to maturity is the process of the constant evolution of CPS intelligence. In the initial stage of its operation. CPS only serves as assistance or decision-support system to the skilled workers. In the mature stage of CPS operation, skilled workers don't need to deal with concrete machining tasks anymore, and they are only responsible for installation, modification and maintenance of CPS.

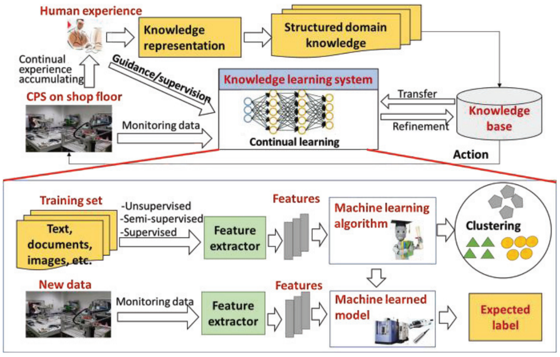

Fig. 4. A framework for knowledge acquisition and learning.

To implement the knowledge learning system, many problem solving methodologies in artificial intelligence such as Case-based Reasoning (CBR) and Machine Learning (ML) can be used. Solving a problem by CBR involves obtaining a problem description, retrieving similar cases by comparing measurement or post-processed data to cases in the case base, reusing the information in the retrieved cases, revising the suggested solution according to specific conditions in target domain, and retaining a new experience to the case base [10]. However, CBR is mainly used to solve problems which cannot be addressed by calculation and deduction. To take full advantage of the large volumes of data generated in shop floor, ML is considered to develop the knowledge learning system. Depending on the nature of learning data, ML can be performed in diverse ways, *i.e.*, unsupervised learning, semi-supervised learning and supervised learning. A typical workflow of ML is depicted in the bottom of Fig. 4. Firstly, the training sets are identified from the large-scale available data. Secondly, the features with multi-granularity are extracted and selected. Then the ML algorithm is performed. For unsupervised learning, grouping of objects is obtained based on some common characteristics. For supervised learning and semi-supervised learning, a machine learned model is trained, and for any an input (new data measured in real-time from CPS), an output (expected label) is acquired. The core of ML is how to extract features and train the models. In the past few years, features are extracted and selected manually, which is a time-consuming task. Currently, deep learning has been developed to replace handcrafted features with hierarchical feature extraction and create models to learn these representations [11].

4. Implementation of CPS architecture

4.1. Description of the shop floor

This section takes a small-scale flexible automated production line in our Micro Manufacturing System Lab as an example to verify the feasibility of the proposed CPS architecture. The flexible automated production line is composed of three machining workstations. Machining workstation 1 is a CNC micro lathe (C000057A lathe) which is used to finish turning process. Machining workstation 2 is a CNC milling machine (MM-250S3 milling) which is used to finish milling and drilling processes. Machining workstation 3 consists of a CNC milling machine (EMCO MILL55) and a KUKA robot. The former is used to finish milling and drilling processes and the latter is used to load/unload workpiece from a conveyer belt.

4.2. Configuration of the CPS

According to the proposed CPS architecture, a solution to CPS physical connection of shop floor based on fieldbus technology and industrial Ethernet is proposed as shown in the left part of Fig.5. Depending on the solution, various sensors, measurement devices, and RFID devices are deployed to the small-scale flexible automated production line to monitor the production environment, as shown in the right part of Fig. 5. Firstly, two noise sensors, two light intensity sensors and three temperature and humidity sensors are deployed for the purpose of monitoring the production environment. Several RFID devices (readers and antennas) are installed on the workpiece buffers for tracking and tracing the workpieces. Meantime, a vernier caliper, a roughometer and a digital dial gauge are deployed in workpiece buffers for inspecting the machining quality of workpieces. A vibration sensor in machining workstation 1, a Janitza power sensor in machining workstation 2, an acceleration sensor, a photoelectric displacement sensor and a camera in machining workstation 3, are embedded on the machine tools for monitoring their working conditions.

On the basis of the configuration of multiple sensors/RFID devices/measurements devices on the lab, a CPS middleware is developed by integrating Java Web, Representational State Transfer (REST) and Arduino platform, thereby realizing the interconnection and interoperability among heterogeneous devices. Note that each machining workstation as well as the sensors has a specific middleware. The representative screenshot of machine monitoring software for Shop Floor is shown in Fig. 6. The sensor data (*e.g.*, power, noise, temperature, and humidity) measured by sensors/RFID devices/measurement devices is transferred to the data server through the middleware. Then these data is processed by the filed PC and the results are presented in the monitor terminals (PC, tablet, mobile phone) through visualization techniques. On the basis of these results, experts can make real-time decisions of production management.

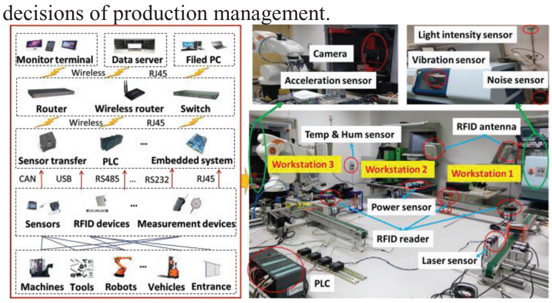

Fig. 5. CPS configuration for intelligent manufacturing shop floor.

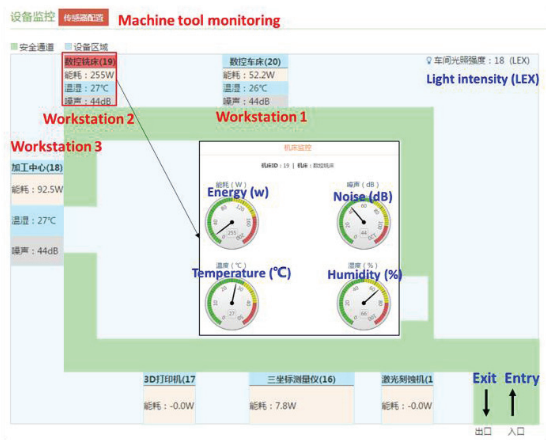

Fig. 6. Machine monitoring software for intelligent manufacturing shop floor.

Based on the virtualization of CPS nodes, enterprise can dynamically release its equipment, and coordinate them to execute different tasks. Besides, customers can receive manufacturing service recommendation and monitor the state of their product orders based on web services and protocols.

5. Conclusion

In this paper, a CPS architecture in shop floor for intelligent manufacturing is proposed. The proposed architecture aims to provide solutions from three key aspects to the configuration and operation of CPS: interconnection and interoperability among different devices, multi-source and heterogeneous data acquisition, integration, processing and visualization, and intelligent decision-making based on knowledge acquisition and learning methodology.

In the future, CPS configuration and operation theory for intelligent manufacturing in shop floor will be further studied based on the proposed CPS architecture. For example, the device discovery based on device abstraction, the control and scheduling of CPS middleware will be considered when a large number of sensors/RFID devices/measurement devices are embedded into shop floor; the evaluation of dynamic manufacturing capability in shop floor will be conducted by processing the condition monitoring data of machining equipment.

Acknowledgments

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